Seasonal adjustment and correction for extreme weather events: the case of quarterly greenhouse gas emissions

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Abstract
The paper illustrates to what extent the existing methodology for the correction for extreme weather events can be applied effectively to quarterly greenhouse gases emissions. Once clarified that not all seasonal fluctuations can be attributed to climatic variations, and that sporadic extreme weather fluctuations cannot qualify as seasonal, the paper reviews existing literature on adjusting time series for extreme weather events, showing to what extent different sectors of the economies can be exposed to the influence of extreme weather conditions, and describing how various elaborations -non-seasonally adjusted, seasonal adjusted and weather normalised data- can serve different needs of the users. The existing methodology for jointly seasonal adjust and correct for extreme weather events is then presented, including an iterative estimation strategy that can be used by national statistical offices.

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The analyses opinions and findings of these papers represent exclusively the views of their authors and do not necessarily reflect those of the OECD or the IMF.

1 Introduction

The paper addresses the questions of whether statistics on quarterly greenhouse gases (GHG) emissions should be corrected for extreme weather events and whether existing statistical methodology can effectively be applied to do this.

Recognizing the need for a timely review of short term evolution of Greenhous Gases (GHG)[1] emissions, Eurostat, the International Energy Agency (IEA), the International Monetary Fund (IMF), the Organisation for Economic Co-operation and Development (OECD), and the United Nations Statistics Division (UNSD) partnered in 2021 to design a consistent methodological approach[2] that could be used to produce seasonal adjusted quarterly GHG emissions accounts by industry and households consistent with GDP statistics (Astolfi et al., 2023[1]). The partnership led to the regular release of quarterly GHG emissions accounts for European Union (EU) countries and macro-regions. Nowadays, seasonal adjusted data are available for non-European economies with a lag of approximately four to five months, starting with the first quarter of 2010[3].

Seasonal adjustment refers to the process of elimination from the raw data of the seasonal fluctuations which result from the composite effect of weather as well as institutional events that regularly repeat every year. The adjusted series show only the variations that are due to long-term trends, business cycles (in the case of economic statistics), and any remaining unpredictable irregular movements. Seasonally adjusted data make it possible to compare the evolution of the series over consecutive periods. The information provided by seasonally adjusted data is crucial for analysts, decision-makers, and forecasters as it captures the core infra-annual movement of the series.

Weather events are usually thought of as following predictable seasonal patterns that repeat in a similar manner every year. For instance, high temperatures characterise summers while low temperature are typically recorded in winter times. Moreover, some weather phenomena, such as snowfalls, only occur in specific seasons whereas others, such as rain, can occur over the course of the year though with higher intensities in certain months.

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[1] GHGs include carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), and fluorinated gases (F-gases). F-gases are hydrofluorocarbons, perfluorocarbons, sulphur hexafluoride, and nitrogen trifluoride.

[2] Detailed methodological notes are available at:

Eurostat: https://ec.europa.eu/eurostat/documents/1798247/6191529/Methodological-note-on-quarterly-GHG-estimates.pdf/6bd54bde-4dd7-ebac-6326-f08c73eb9187?t=1644394935594;
IMF: https://climatedata.imf.org/datasets/543872e1d86c49e3a3bdf38f2b758f92_0/about
OECD: https://www.oecd.org/sdd/eea/Methods-Note-Producing-OECD-Quarterly-Air-Emission-Accounts.pdf

[3] Quarterly GHG emission data are available for the three organisations at:

Eurostat: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Quarterly_greenhouse_gas_emissions_in_the_EU

IMF: https://climatedata.imf.org/datasets/543872e1d86c49e3a3bdf38f2b758f92/explore

OECD: https://stats.oecd.org/Index.aspx?DataSetCode=OECD-AEA

Usual weather events are typically predictable though they may vary significantly from place to place on the globe. However, other weather events may occur sporadically with unusual and unpredictable intensities that significantly deviate from their typical seasonal patterns. Such events are called “extreme weather” events. They are defined by Intergovernmental Panel on Climate Change (IPCC)[4] as:

> *"An extreme weather event is an event that is rare at a particular place and time of year. Definitions of rare vary, but an extreme weather event would normally be as rare as or rarer than the 10th or 90th percentile of a probability density function estimated from observations. Obviously, the characteristics of what is called extreme weather may vary from place to place in an absolute sense. (Seneviratne et al., 2021[2])*

Temperature, for instance, can reach exceptional high or low levels that may persist across several days. Such phenomena, called heat or cold waves, generate increasing concern. The World Meteorological Organization (WMO) established a task team in 2010 that proposed the following definitions for a heat and cold waves:

> *"A marked unusual hot weather (Max, Min and daily average) over a region persisting at least two consecutive days during the hot period of the year based on local climatological conditions, with thermal conditions recorded above given thresholds".*

and,

> *"A marked and unusual cold weather characterized by a sharp and significant drop of air temperatures near the surface (Max, Min and daily average) over a large area and persisting below certain thresholds for at least two consecutive days during the cold season." (Añel et al., 2017[3])*

These definitions emphasise the local features of what may be considered an extreme weather event, implying that while a value of temperature may be considered extreme for a given part of the globe, it may be completely normal for another. Even if weather forecasters can anticipate approaching extreme weather events by a few days, these kinds of phenomena remain by their own nature erratic and normally cannot be predicted far ahead[5].

Although climate change and weather events are related, the WMO clarifies that the term “weather” describes the short-term events of the atmosphere whereas “climate” refers to the events of atmosphere occurring over relatively long periods of time, typically 30 years. The occurrence of extreme weather events has often been attributed to the impact of anthropogenic[6] climate change, for instance by Peterson and colleagues (2013[4]) and IPCC (2013[5]). A major concern is that the frequency, intensity, and length of extreme weather events will further increase by the end of the current century.

Extreme weather events may result in natural hazards such as floods, drought, landslide, mudslide, or avalanche which in turn may lead to disasters, including loss of human and animal lives or severe material damage. However, natural hazards and related disasters are out of scope of the present study because it focuses on statistical methods that may be used to adjust quarterly GHG emissions resulting from anthropogenic activities.

[4] For more information on the IPCC see https://www.ipcc.ch/

[5] The IPCC 5th Assessment Report (WG 1 Glossary) differentiates extreme weather from extreme climate events. “When a pattern of extreme weather persists for some time, such as a season, it may be classed as an extreme climate event, especially if it yields an average or total that is itself extreme (e.g., drought or heavy rainfall over a season)."

[6] Resulting from human activity.

2 Should we adjust quarterly greenhouse gas emissions for extreme weather events?

Seasonally adjusted data make it possible to compare the evolution of the series over consecutive periods of time. However, seasonal adjustment procedures do not eliminate all weather-related movements in the data. In fact, they only eliminate predictable and recurrent seasonal fluctuations. Any extreme weather event, such as prolonged heat waves or extremely cold winters, will remain in the seasonally adjusted data as part of the irregular component.

This section addresses the question of whether statistics on seasonally adjusted quarterly greenhouse gases (GHG) emissions should be corrected for extreme weather events. It starts by looking at the literature on other instances where corrections for extreme weather events have been applied, and then considers the case for applying such corrections to quarterly GHG data.

Extreme weather adjustments for economic time series

To the best of our knowledge, only two papers (Boldin and Wright, 2015[6]) and (Pang, Bell and Monsell, 2022[7])) propose an integrated approach that combines seasonal adjustment and correction for extreme weather events for economic data. All other studies on the influence of extreme weather events on infra-annual statistics rely on seasonal adjusted figures looking at the influence of unusual weather events on quarterly GDP[7], on the construction and energy sectors and on retail sales. These studies are discussed below.

Quarterly GDP

All papers studying the impact of unusual weather events on quarterly GDP were published around 2014, possibly because of the need to disentangle the post 2008 financial crisis business cycle fluctuations from the impact of the particularly harsh winter weather conditions that occurred across December 13 and January 2014. Noteworthy the fact that all studies used seasonal adjusted figures as starting point. Ouwehand and Van Ruth (2014[8]) analysed the impact of weather events on the Dutch seasonal adjusted quarterly GDP and value-added data on the national and sectoral level. They investigated the possible impact of temperatures, precipitations (both rain and snow), and sunny or cloudy days. Only temperature-related weather effects were found to have influenced the economy significantly on a quarterly basis. Significant temperature-related indicators included the so called “degree days”, defined as the sum of the deviation of the daily average temperature from 18°C and the number of frost days (i.e. of days with a

[7] Dell et al (2014) provide an extensive review of the literature exploring the impacts of climate change on agricultural output, industrial output, labour productivity, energy demand, health, conflict, and economic growth, among other outcomes. As those studies focus on annual data, they are considered out of scope.

minimum air temperature below 0°C). Estimating a regARIMA model, Ouwehand and Van Ruth found that frost days had a negative impact on manufacturing whereas energy related sectors had been affected in the opposite direction due to the increased demand for heating. As a result, the overall impact on economy as a whole was relatively small.

A similar approach was used by the Bundesbank analysing the impact of weather conditions on German quarterly GDP (Deutsche Bundesbank, 2014[9]). Looking at the number of frost days as a proxy for harsh weather conditions, researchers at the Bundesbank found that an extra frost day lowered GDP by just under 0.03% in the fourth quarter of 2013 and by around 0.07% in the first quarter 2014. The different impact across the two quarters may be explained by the rigidity of aggregated demand due to the end-year festivities (Christmas and New Year). When analysing the impact at sectoral level, they reported that constructions was the most affected sector, with smaller impact recorded by manufacturing and services. They also found that a positive effect on the energy production sector.

Bloesch and Gourio (2015[10]) investigated the impact the 2013-14 winter on the US economy using a fixed effects regression model on seasonal adjusted data. They concluded that the overall effect of weather variables on the economy as a whole was limited and therefore t other factors must have been at play to explain the weak performance of the USA GDP at the beginning of the year 2014. When extending their analysis to the economic sectors, they found that weather had had a significant, albeit short-lived, impact only on a few industries, including utilities, construction, hospitality, and, to a lesser extent, retail.

The construction sector

Papers focusing exclusively on the construction sector considered the impact that abnormal temperatures and precipitations (rain and snow) might have on housing starts, completions or prices either at national or regional level, typically finding stronger evidence of such an influence at local level. The Eurostat *Handbook on Seasonal Adjustment* (European Commission Eurostat, 2018[11]) mentions the correction for the influence of extreme weather conditions only in relation to constructions.

Cammarota (1989[6]) identified the existence of significant albeit small influence of unseasonable weather on house started broadly differentiated winter from summer effects. Cammarota further refined the analysis to detect a significant impact of weather anomalies on housing starts in the first months of the year only, particularly at a regional level, with no evidence in subsequent months.

Using a vector autoregression (VAR) approach, Coulson and Richard (1996[12]) tried modelling temperature, precipitation, housing starts, and housing completions simultaneously for each of the analysed regions founding that temperature shocks were more prominent in cold regions, precipitation mattered more than temperature in the South, and that neither mattered much in the West.

In confirming some of the previous results, Fergus (1999[13]) noted that abnormal had a substantial contemporaneous effect on housing starts in January and February while abnormal precipitation had a significant impact in June and December, confirming that the impact of temperature and precipitations varies by region. Unlike the previous papers, however, he found that there were statistically significant lagged adjustments that in many cases offset the contemporaneous weather effects, suggesting that the long-term effect of abnormal weather is not so pronounced.

The energy sector

Finally, we found a lot of research analysing the impact of extreme weather events and climate change on the energy sector. Two types of impacts have been studied (Añel et al., 2017[3]):

On the one hand, extreme weather phenomena affect energy production and its facilities as either cold or heat waves can generate increase in the demand for energy and, as a result, boost GHG emissions. During heat waves, high temperatures can affect the generation capacity of fossil fuel and nuclear-powered plants, as well to renewable technologies, due to increased air and water temperature. When the air temperature becomes very high, fuel efficiency is affected due to a lower oxygen concentration in the air. At the same time, also nuclear-powered plants might be affected by raising temperatures due to the reduced thermal efficiency of the plants and also because plants may experience refrigerating problems. Finally, high temperatures can impact on the efficiency of the transmission and distribution systems. The generalised loss in efficiency may result in an increase of GHGs emissions. All that associated with likely increase in the demand for energy caused by more intense use of coaling systems.

On the other hand, the extreme weather conditions can stress the system for production of energy to the extent to induce blackouts, which will have the opposite effect in terms of GHG emissions.

Cold waves can also affect the energy sector generating breakdowns in power plants or reducing oil and gas production. Moreover, they could also cause failures in airlines and towers, as ice and snow may accumulate in the insulation under freezing conditions, bridge them and cause a flashover.

Retail sales

Several papers studied the influence of weather events on retail sales in Europe. These included the impact of unexpected temperature deviations on apparel sales in France ((Bertrand, Brusset and Fortin, 2015[14])); on sporting goods in Finland and Switzerland (Appelqvist et al., 2016[15]); the role of temperatures as well as precipitations (rain and snow) on food and fashion retail in a region of Germany (Arunraj and Ahrens, 2016[16]) and on sales forecasting for e-commerce for a large European fashion retailer (Steinker, Hoberg and Thonemann, 2017[17]) or overall consumer spending in Swiss retail sales (Sandqvist and Siliverstovs, 2021[18]). All in all, studies on retails sales suggest that the effects of abnormal weather differ across seasons. Moreover, an interesting feature of these studies is the attention to the lagged adjustments, meaning that a decrease in retails associated to the impact of weather events may be offset by a symmetric increase as soon weather conditions go back to normal levels.

The case for making extreme weather adjustments to quarterly GHG emissions

When users observe abnormal movements in the seasonal adjusted data, a frequent enquiry is whether the anomalies can be explained by weather events. Quarterly GHG emissions can indeed be affected by unusual weather events, either during the winter or the summer season, due for example to the extraordinary use of fossil energy sources for heating or coaling by households and firms.

The purpose of weather correction is precisely to help users to better understand the underlying movements in the data by producing time series that could be interpreted as a representation of what would have happened if weather conditions had been at their average values for the season. As a result, changes in the series from one period to the next are not due to abnormal weather conditions.

Whenever quarterly GHG emissions are estimated indirectly using temporal disaggregation techniques, a valuable strategy is to weather correct the predictor indicators. Such an approach allows a detailed analysis of the possible impact of the unusual weather events in terms of either frequency of the data, as monthly or even daily data could be corrected, or geographical disaggregation where local data could be used instead of national data.

However, should users be interested in the most accurate estimates of the actual levels of the emissions, that do reflect the extra movement due the impact of seasonal fluctuation and unusual weather events, raw figures should be preferred to the weather corrected and seasonal adjusted series. As producers of official statistics aim at meeting the need of all users, all possible elaboration should be released, including raw, seasonal adjusted and seasonal adjusted and weather correct series.

In reviewing exiting practices, we found that only the Australian Department for Climate Change and Energy Efficiency releases infra-annual seasonal adjusted GHG emissions also corrected for unusual weather conditions (Australian Government Dep of Climate Change, 2011[19]). Of note, however, the afct that the correction is limited to the effects of abnormal temperatures ("heating degree days" and "cooling degree days") capturing the resulting demand for extra heating and cooling, and hence emissions. The significance of explanatory variables capturing temperature anomaly is tested in SEASABS[8] using a regression approach prior to seasonally adjustment and trend-cycle extraction. The effect of the statistically significant variables is then entered as a "prior factor" and removed from the seasonally adjusted and trend series.

There are three possible reasons why quarterly GHG emissions estimates have not been adjusted in other countries: first, users may not demand such information, as discussed above; second, the estimation of quarterly seasonal adjusted GHGs emissions itself is quite recent, and not many countries have yet produced such estimates[9]; and third, despite the extensive literature on either seasonal adjustment or analysis of the influence of extreme weather events, the two issues have seldom been analysed in an integrated manner.

[8] SEASABS is an ABS software package (McLaren, McCaskill and Zhang, 2006[9]).

[9] The international task force started in 2021. Only a few countries had implemented the production of quarterly GHG emissions series, including the Netherlands, Sweden, Australia, New Zealand and more recently the UK. Eurostat and the IMF started publishing quarterly estimates at the end of the year 2021 followed by the OECD in 2022.

3 Can we adjust quarterly greenhouse gas emissions for extreme weather events?

Existing methods

Capturing the impact of extreme weather and climate events

From a statistical standpoint, disentangling the relative impact of usual seasonal fluctuations, climate change and extreme weather events on time series is a challenging task. Boldin and Wright (2015[6]) state "the idea of preventing unusual weather from affecting seasonal factors is a little tricky in the presence of climate change, because unusual weather might change one's beliefs about seasonal norms".

Classical time series analysis is well equipped to address this issue in that climate change and weather events would affect to different extents the subcomponents of the time series such as trend, seasonal or the irregular depending on the frequency of the events. For instance, a continuous increase in average temperature across all months of the year and occurring over several years may determine a change in the trend component of the time series, whereas an increase of the highest temperatures recorded in the same month for several years may determine a change the variability of the seasonal component of the series. Finally, isolated hot months are typically included as outliers and assigned to the irregular component, unless a specific analysis is conducted.

Immediate impact vs bounce-back effect

Several studies aiming at isolating the impact of extreme weather events on time series (particularly on Economic time series) have considered the so called "bounce back effect", meaning that the immediate impulse generated by the abnormal weather event and resulting in a decrease (or increase) in the time series of interest, may in some cases be followed by increase (or decrease) that offset the initial impact. For instance, a decrease in retail sales due to extremely heavy rains may be compensated by an above average level of sales in the following days should the weather conditions return to normal patterns. Similarly, the negative impact on GDP caused by particularly harsh winter conditions recorded in the first quarter of a year may be followed by an increase of equal magnitude in the next quarter (Bloesch and Gourio, 2015[10]). In the case of greenhouse gases (GHGs), however, we tend to exclude such a bounce-back effect as above average emissions induced by extreme hot or cold waves are unlikely to be compensated by a return to normal temperature.

Conceptual framework for infra-annual GHG data

Quarterly GHG accounts are indirectly calculated using temporal disaggregation techniques following the indirect approach commonly applied in the compilation of other quarterly statistics including, among others, quarterly national accounts. The indirect approach is typically used if the procedure used to estimate the annual data cannot be replicated for the corresponding sub-annual estimates because a full set of sub-annual (monthly or quarterly) data is not available, as in the case of GHG emissions.

The basic principle of temporal disaggregation is to interpolate the GHGs time series from the annual estimates of Air Emissions Accounts (AEAs)[10] into quarterly values (backward series) and to extrapolate those quarters for which annual accounts are not yet available (forward series). The procedure shares similar properties and the same kind of techniques as those used in benchmarking. Both steps, interpolation and extrapolation, are performed with auxiliary information, that is, sub-annual (monthly or quarterly) "predictor-indicators," which are considered sufficiently suited to approximate the quarterly developments of GHG emissions. The GHG emissions accounts can best be described as a four-dimensional data cube consisting of geography, GHG, activity (industries and households), and time.

Prior to their use as inputs in our temporal disaggregation, the predictor indicators are seasonally adjusted (including calendar and working day adjustment). As some predictor indicators are available a monthly and even daily frequency, it is preferable to seasonal adjusting the predictor indicators at their highest available frequency rather than the estimated quarterly variables resulting from the temporal disaggregation. Such a strategy allows capturing and adjusting seasonal and weather-related fluctuations that might otherwise be missed should more aggregated data be used.

Seasonal adjustment techniques

Methodological approaches to seasonal adjustment of time series can be clustered into two broad categories: model-based and empirical techniques.

Model-based techniques assume that time series can be decomposed into unobserved components, typically including trend-cycle (TC_t), seasonal (S_t) and irregular (I_t) components. The estimation of these components is seen as a problem of signal extraction. Following the original proposal of Wiener and Kolmogoroff, such techniques have been implemented in the TRAMO-SEATS programme by Gomez and Maravall and in the STAMP programme by Koopman et colleagues.

On the other hand, empirical techniques use statistical smoothing methods without assuming the existence of a data generation process. One of the most widely used programmes embedding the empirical approach had originally been developed at the US Census Bureau (2017[20]) in the late sixties and has extensively evolved over time to the extent that its most recent version (X-13ARIMA-SEATS)[11] also features model-based elements derived from the SEATS programme by Gomez and Maravall (1994[21]).

The most recent advancement in terms of programme development is JDemetra+, a tool developed by the National Bank of Belgium (NBB) in cooperation with the Deutsche Bundesbank and Eurostat in accordance with the Guidelines of the European Statistical System (ESS)[12]. JDemetra+ implements the concepts and algorithms of both TRAMO/SEATS and X-12ARIMA/X-13ARIMA-SEATS.

The latest versions of the all the programmes mentioned above can be used to implement the regARIMA approach described in the remainder of this section.

[10] The AEAs are compiled by countries for the international standard known as the System of Environmental-Economic Accounting (SEEA).

[11] The software X-13ARIMA-SEATS is available at https://www.census.gov/data/software/x13as.html

[12] The latest JDemetra+ released version can be downloaded at: https://github.com/jdemetra

The econometric framework

The regression-ARIMA approach (regArima) is widely used in the literature to combines in a single econometric framework the adjustment for regular infra-annual seasonal fluctuations along with the adjustment for the influence of calendar effects and any other sporadic event. As a result, the seasonal ARIMA (*p,d,q*)(*P,D,Q*) model is augmented by the addition of exogenous linear regression variables to capture the influence of trading and working days, leap year, national holidays occurring either at fixed dates (e.g. Christmas) or moving with respect to the Gregorian calendar (e.g. Easter, Ramadan or the Chines new year festivities), or any errant event, such as strikes, that may alter the identification of the trend-cycle components of the time series. As such, the set of regression variables can also include weather related variables (Pang, Bell and Monsell, 2022[7]) able to explain significant deviations from weather conditions expected in each season.

Therefore, a general reg-ARIMA model can be formulated as

$$\phi(L)\Phi(L^s)(1-L)^d(1-L^s)^D\left(y_t - \sum_i \beta_i x_{i,t}\right) = \theta(L)\Theta(L^s)\varepsilon_t$$

where $\phi(L)$ and $\Phi(L^4)$ are the nonseasonal and seasonal autoregressive (AR) polynomials of finite order *p*; *P*, $\theta(L)$ and $\Theta(L^4)$ are the nonseasonal and seasonal moving average (MA) polynomials of order *q* and *Q*; *d* and *D* are the integer nonseasonal and seasonal difference operators, L is the lag operator (i.e. $L^s y_t = y_{t-s}$, with s=4 for quarterly or 12 for monthly data), and ε_t is an independent and identically distributed error term with zero mean and constant variance σ^2. β_i are the coefficients obtained from a linear regression of y_t against the set of calendar or weather regressors $x_{i,t}$. Notice that the set of weather regressors includes no lagged variables assuming that the impact of extreme weather conditions on the emissions of GHGs is only contemporaneous.

The regression ARIMA model can be thought of either as generalization of a ARIMA model to allow for regression mean functions $\sum_i \beta_i x_{i,t}$, or as generalized regression model to allow the errors $z_t = y_t - \sum_i \beta_i x_{i,t}$to follow a seasonal ARIMA model which addresses the possible presence of autocorrelation in the residuals.

An iterative estimation strategy

The estimation strategy can be based on an iterative approach towards an optimal model specification. In empirical research, iterations typically follow either a top-down or bottom-up procedure. In the former, a model including all candidate regressors is first estimated to then remove insignificant regressors iteratively to arrive at the optimal specification. In the bottom-up procedure, on the other hand, models including individual candidate regressors are first estimated to retain only significant regressors. Based on the initial selection, sets of multiple regressors are further tested to arrive to the optimal specification. For the purposes of the regArima specification problem, Pagan and colleagues (2022[7])suggest opting for the bottom-up procedure. Therefore, the reminder of this section describes in further detail the iterative bottom-up estimation strategy.

Before starting to assess the significance of individual regressors, a preliminary phase requires the estimation of a benchmark specification that includes no regressors. The time series of interest is therefore fitted with airline model SARIMA(0,1,1)(0,1,1)$_S$ using default options from X11 (**Step 1** in figure XX below). Such a benchmark specification allows identifying:

- Log transformation
- Trading/working days

- Easter effects
- Leap year
- Outliers

as well as calculating the F-adjusted version of the Akaike Information Criteria (AICC) that will be used in the subsequent steps to compare the benchmark model against competing specification in the following steps.

Holding the benchmark specification (i.e. leaving unchanged log transformation, outliers, trading/working days, Easter effects and Leap year), the airline model is re-estimated as many times as the number of available candidate regressors adding each of them one at the time (**Step 2**).

Should the time series to be modelled cover a sufficiently long timespan, it would be recommendable to replicate step 2 on two additional but disjoint sub-spans, each covering half of the full sample. The comparisons across the three resulting samples (first half, second half and full sample,) allows cross validating the results or identifying possible breaks and structural changes in the original series (**Step 3**).

To assess whether the inclusion of weather regressors improves the model specification, the AICCs associated to each specification are compared and only if the specifications showing a reduction in the AICC of at least 5 points are retained. Should the two sub spans mentioned in step 3 above be available, the same comparison based the AICC should be applied across all three samples. (**Step 4**)

For all retained models, the t-statistic is used to verify the significance of the parameters (|t-stat|>2) and, should a parameter be significant, its sign is checked against expectations. In addition, any significant change in the parameters of both annual and seasonal moving average components (MA_Y and MA_S) should be scrutinised. As for step 4, also in this case the checks should be extended to all available time sub-spans (**Step5**).

Next is the analysis of the outliers. The hypothesis is that some of the outliers originally identified for the benchmark model (Step 1) could indeed be explained by some extreme weather events. Should that be the case, the number of outliers in the models that include the weather regressors is expected to reduce. That said, care should be paid to new outliers that may have emerged or whether the type of outliers[13] originally identified in the benchmark model had changed as result of the introduction of the new weather regressors (**Step 6**).

It is possible that the influence of some weather regressors could be more accentuated in specific parts of the year. To verify such a hypothesis, month specific regressors can be used (**Step 7**). They are built as dummy variables assuming the value of the original weather regressor only in the months of interest:

$$V_t^{(m)} = V_t \; for \; month \; m \; and \; 0 \; otherwise$$

Where *m =1,…, 12* represents the months of the year. The resulting twelve month-specific indicators can then be individually tested for each weather regressors by repeating the procedure for the weather regressors as described above (**Steps 8 to 11**). Any months that would produce singularities in the regression matrix (i.e., the values for that month were 0 over the entire modelling span) should be omitted. Only models with significant parameters and that reduce the AICC should be retained. This part of the bottom-up estimation strategy concludes the analysis of individual regressors.

The second and last part of the procedure checks for the simultaneous inclusion of multiple regressors. To keep the exercise manageable, only sets of up to a limited number of regressors are considered (e.g. up to 4 regressors). Should it be possible to cluster the regressors on the basis of their characteristics (e.g.

[13] The most common type of outliers include: Additive outlier (AO), Transitory Change (TC), Level Shift (LS) and Seasonal Outlier (SO)

temperature, precipitation, snow), an additional constraint can be added in that at least one regressor for each cluster should be included in sets larger or equal to the number of cluster. (**Steps 12 and 13**).

Finally, the procedure assesses whether the inclusion of the best set of weather regressors bring an actual improvement as compared to the simple seasonal adjustment procedure with no correction for extreme weather conditions. To do that, the specification including the best performing set of weather regressors is estimated with no constraint on the outliers. An initial graphical inspection is performed by overlapping series the seasonal adjusted series with no weather regressors (SA) with the that resulting from the best performing specification including weather related regressors (SWA). Such a graphical inspection allows verifying the relative smoothness along with a comparison of location and type of outliers (**Step 14**). The graphical inspection is completed by the analysis of the chart displaying the ratios od SA/SWA ratios by month (**Step 15**): large variabilities by month may indicate that the impact of the weather correction is more pronounced in specific parts of the year (typically the winter and summer months). Similar indications may come from the average absolute percent difference between the SA and SWA series computed by month (**Step 16**). In this case, months exhibiting average differences above 10 percent may suggest the presence of a significant correction for weather conditions.

1. **Base Model**: fit an airline model SARIMA(0,1,1)(0,1,1)) , with default options from X11 on the full sample, to identify:
   - Log transformation
   - Outliers
   - Trading days effect
   - Easter effect
   - Leap year effect

   SAVE specification and AICC

2. W models: fixing
   - Log transformation
   - Outliers
   - Trading days
   - Easter effects
   - Leap year

   from step 1, fit airline models with the addition of one weather regressor at the time.

3. In addition to the full sample, repeat step 2 onto two disjoint sub spans of equal length to cross check results

4. Check ΔAICC (AICC Base model-AICC vs W models)

   Retain models where ΔAICC<-5 simultaneously for the full-sample and the two sub spans

5. Check the sign of beta, its significance (|t-stat|>2) for the full-sample as well as for the two sub spans

   Compare parameters of the MA_Y and MA_S Check for significant changes

6. Outliers

   Verify if outliers identified in stage 2 are confirmed or If some disappear because captured by the weather regressors

7. Built month specific regressors for each weather regressor

   $$V_t^{(i)} = V_t \; for \; month \; i \, , \quad = 0 \; otherwise$$

8. Fit each month specific weather regressors in the airline model as in step 3

9. Check **t-stat** month-specific regressors using the full sample as well as the two sub spans.

   Omit any month that would produce singularities in the regression matrix (i.e., the values for that month were 0 over the entire modelling span) were omitted

10. Re-fit the model retaining only the significant variables

    Compared AICC against the baseline model and those using the original regressors

11. Check sign of beta, its significance (|t-stat|>2) for the full-sample as well as the two sub spans

12. Set multiple regressors

    Cluster weather regressors (e.g. temperature, precipitation, snow) then make sets of up to 4 regressor. For sets with 3 or 4 regressors at least one for each cluster

13. Repeat steps 2 to 11 and select models including multiple regressors using the min AICC criteria

14. Final comparison SA vs SWA

    X-11 with setting determined by X-13ARIMA SEATS Outliers free

    Graphical inspection to check AO and LS

15. Ratio by months

16. Calculate Average absolute percent difference by month for the full sample and the sub spans an check if any month exceed 10%

4 Conclusions

Weather correction can help users to better understand the underlying movements in data. Resulting time series could be interpreted as a representation of what would have happened if weather conditions had been at their average values for the season, so that changes from one period to the next in the seasonal adjusted data can be directly compared.

This paper has investigated whether currently existing statistical methodology allows modelling in an integrated way both regular seasonal fluctuations (including calendar effects) and extreme weather events when estimating quarterly greenhouse gases (GHG) emissions.

We argue that regARIMA methodology is well suited to the task and offers a valid tool that not only permits to seasonal adjust and correct for extreme weather events historical time series but also differentiating the impact of long-term climate change from that of short-term weather events.

The regARIMA methodology has been widely used in official statistics to correct raw data for calendar effects and for the identification of outliers, so that a large body of applied experience is currently available worldwide. Based on the experience developed by the US Census Bureau (Pang, Bell and Monsell, 2022[7]), we propose a standard estimation strategy that may allow standardising current practices.

5 References

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